

Data Science

Capstone Project 2:

MECHANICAL FITTING FAILURE CLASSIFICATION PROBLEM

Content:

1. Notebook for the Project:

[https://github.com/psanghal/Springboard-Data-Science/blob/master/Capstone Project 2/Project Notebook %26 Data/Capstone Project 2-Mechanical Failure.ipynb](https://github.com/psanghal/Springboard-Data-Science/blob/master/Capstone%20Project%202-Mechanical%20Failure.ipynb)

(**Please copy and paste the full link directly in the browser to view the notebook**)

2. Presentation Slides Deck:

<https://drive.google.com/file/d/1FJYKwK8z-ZFDITe1wgpGVub06fpNjbJo/view?usp=sharing>

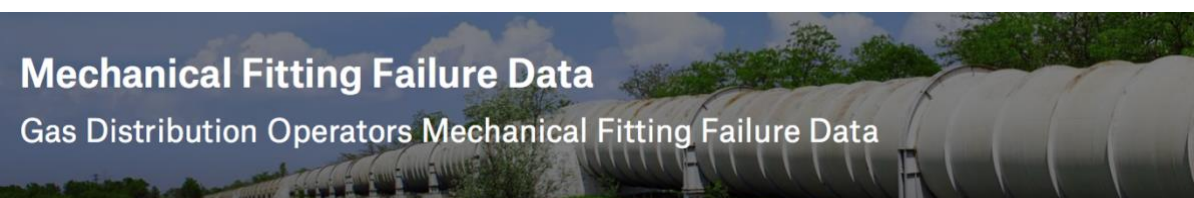
3. Consolidated Report (See Enclosed)

*Prepared by:
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Problem Statement: Code of Federal Regulations (49 CFR Parts 191, 192) requires gas distribution pipeline operators to submit reports on an annual basis of all hazardous leaks that involve a mechanical fitting (DOT Form PHMSA F-7100.1-2).

Our goal is to classify mechanical fitting failure in the gas pipeline so that we can identify in-advance reasons that could have caused the leak to happen, when, and may be how often after the installation date?

If there are any fittings that failed during the first year of operations, then that issue could either be related to design defect or material defect supplied by a third party, which should get reported to the CFR in a prompt manner.



Benefit to Clients: This report contains 326 pipeline operators and 225 manufacturers who are directly or indirectly involved in transporting gas to various locations using their pipeline network safely, reliably and long-term for their customers.

By training this model, we will help clients proactively manage their repair/ maintenance schedule on specific fittings that are impacted. Allow clients to engage manufacturers in research and development of long-life fittings. Develop capability to set up early leak detection system which can help us avoid environmental hazards.

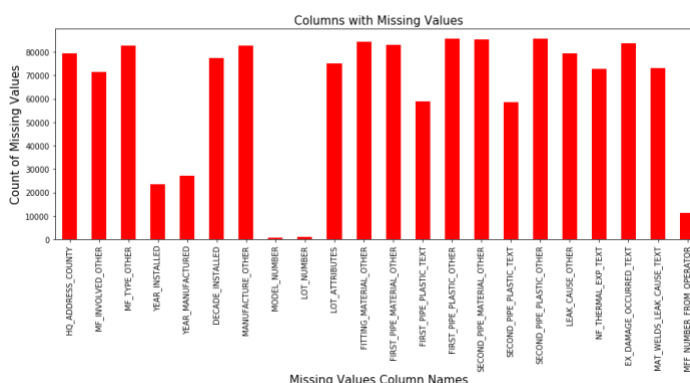
This report can also be helpful in estimating operator's insurance premium based on operational performance.

Data Story:

This dataset was available on Kaggle in comma separated value, csv format. My mentor discovered this dataset and recommended me to work on it. This dataset contained 85,611 observations and 54 columns detailing various attributes about mechanical fittings used in the gas pipeline, some as old as 165 years old.

One of the major challenges with this dataset was that it was entirely in text format. As an example, failure date when the leak occurred, installation date when the fittings were installed and pipe nominal sizes, all were presented in the text format which had to be transformed into date time and numerical values.

Moreover, there were multiple columns where information regarding leak and the manufacturers were captured in two separate columns. One represented by column label ending with _TEXT while the other as a subset represented by _OTHER. The columns ending with _TEXT had multiple missing values which had to be replaced by values in the _OTHER columns.



To get a better understanding of the missing values, I wrote a function missing_dashboard which gave an overview on missing columns and unique values as shown in the table below.

The size of this table is dependent on a user defined variable 'missing_percentage' which can be selected anywhere between 0 to 1. For this table as an example, I chose 0.7 as the missing_percentage, which collected information on 15 missing columns out of 22 columns.

Average (base) Missing Percentage: 0.73
Number of Missing Columns
(Missing Percentage at 0.7): 15

	missing_values	missing_percentage	unique_values_in_missing_columns	available_values_in_missing column
HQ_ADDRESS_COUNTY	79345	0.93	84	6266
MF_INVOLVED_OTHER	71434	0.83	731	14177
MF_TYPE_OTHER	82557	0.96	317	3054
DECADE_INSTALLED	77247	0.90	10	8364
MANUFACTURE_OTHER	82683	0.97	196	2928
LOT_ATTRIBUTES	83343	0.97	723	2268
FITTING_MATERIAL_OTHER	84411	0.99	52	1200
FIRST_PIPE_MATERIAL_OTHER	82845	0.97	41	2766
FIRST_PIPE_PLASTIC_OTHER	85557	1.00	24	54
SECOND_PIPE_MATERIAL_OTHER	85274	1.00	53	337
SECOND_PIPE_PLASTIC_OTHER	85568	1.00	16	43
LEAK_CAUSE_OTHER	79267	0.93	778	6344
NF_THERMAL_EXP_TEXT	72766	0.85	2	12845
EX_DAMAGE_OCCURRED_TEXT	83503	0.98	2	2108
MAT_WELDS_LEAK_CAUSE_TEXT	73060	0.85	2	12551

As we can see above, there are multiple unique values in the missing columns which can be used to replace missing values in other columns. To find this out, I wrote a function to help identify missing replacement values from _OTHER columns to fill missing values in the _TEXT column.

1. missing_value_replacement
2. missing_value_index_from_column_1
3. getvalues_from_column_2_using_missing_index_from_column_1
4. missing_replacement_value_and_index_column_2

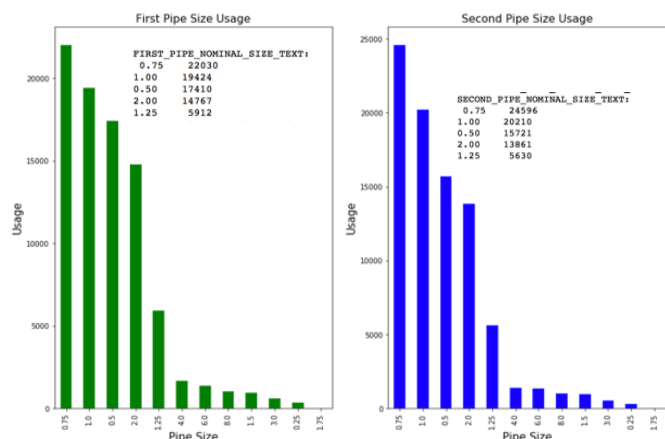
As a result, we were able to replace a total of **18,789** missing values in a total of 9 columns.

Exploratory Analysis:

After replacing some missing values, my focus shifted on wrangling dates and getting insights from the data. I was interested in exploring which states in the US had maximum number of leaks by manufacturers. Which Manufacturers accounted for maximum number of leaks and what was the primary cause for the leak. Below, are some exploratory graphs which will help us answer these questions.

- **Most Used Pipe Sizes:**

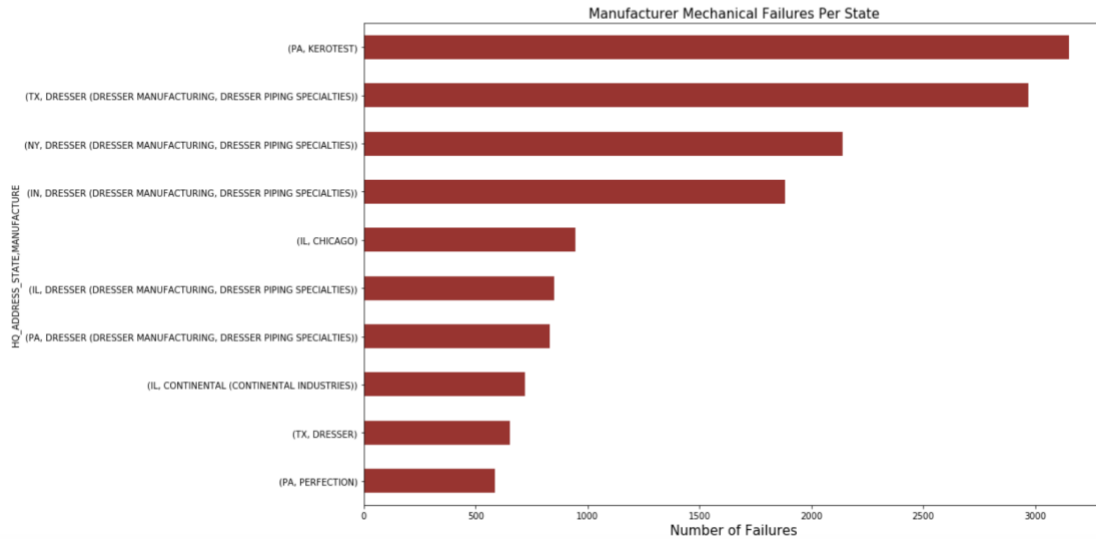
After converting pipe size from text format to numerical values, pipe size of 0.75 showed most usage among pipeline operators with a transactional activity of 22k to 24K over the years.



- The Top 10 Known Manufacturers by State where Leak Occurred:

HQ_ADDRESS_STATE	MANUFACTURE	
PA	KEROTEST	3152
TX	DRESSER (DRESSER MANUFACTURING, DRESSER PIPING SPECIALTIES)	2972
NY	DRESSER (DRESSER MANUFACTURING, DRESSER PIPING SPECIALTIES)	2138
IN	DRESSER (DRESSER MANUFACTURING, DRESSER PIPING SPECIALTIES)	1881
IL	CHICAGO	944

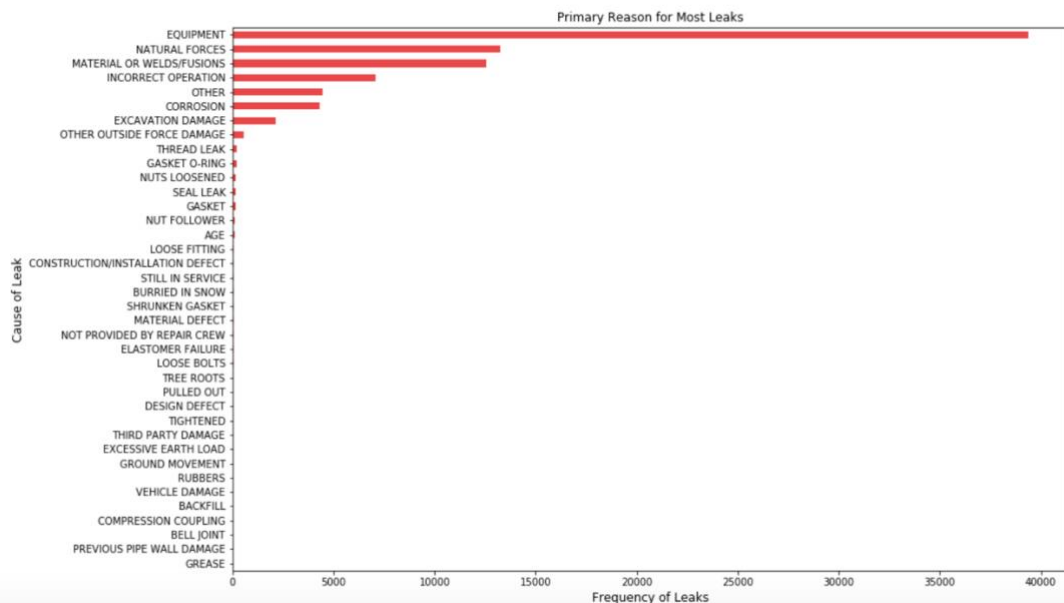
Name: MANUFACTURE, dtype: int64



- Top 15 Reasons for the Leak:

****Top 15 reasons for leak****

	Reason_Count	% Reason_Count
EQUIPMENT	39370	45.987081
NATURAL FORCES	13230	15.453622
MATERIAL OR WELDS/FUSIONS	12551	14.660499
INCORRECT OPERATION	7070	8.258285
OTHER	4464	5.214283
CORROSION	4330	5.057761
EXCAVATION DAMAGE	2123	2.479822
OTHER OUTSIDE FORCE DAMAGE	575	0.671643
THREAD LEAK	225	0.262817
GASKET O-RING	223	0.260481
NUTS LOOSENED	180	0.210253
SEAL LEAK	163	0.190396
GASKET	144	0.168203
NUT FOLLOWER	133	0.155354
AGE	90	0.105127

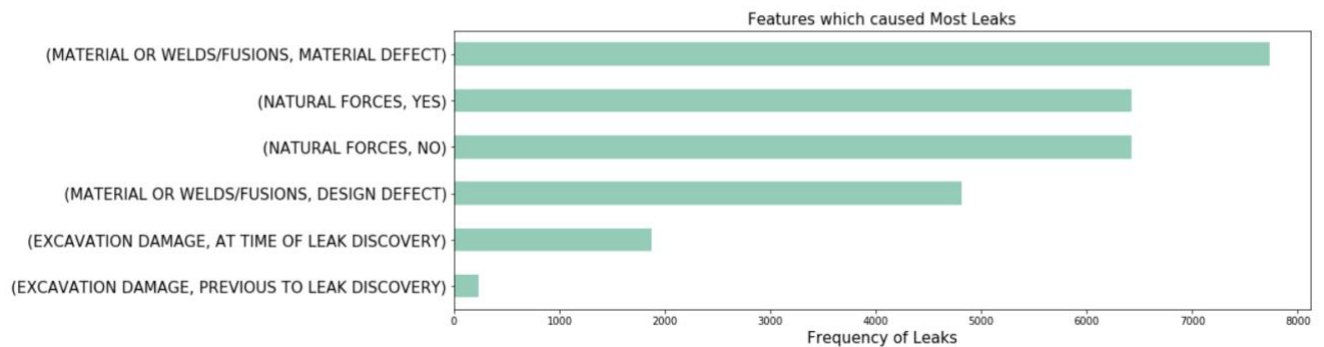


- **Features which Caused Leak in the Pipeline:**

****Features which caused leak****

LEAK_CAUSE_TEXT	ADDITIONAL_LEAK_FEATURES	Feature_Count \
MATERIAL OR WELDS/FUSIONS	MATERIAL DEFECT	7734
NATURAL FORCES	YES	6424
	NO	6421
MATERIAL OR WELDS/FUSIONS	DESIGN DEFECT	4817
EXCAVATION DAMAGE	AT TIME OF LEAK DISCOVERY	1872
	PREVIOUS TO LEAK DISCOVERY	236

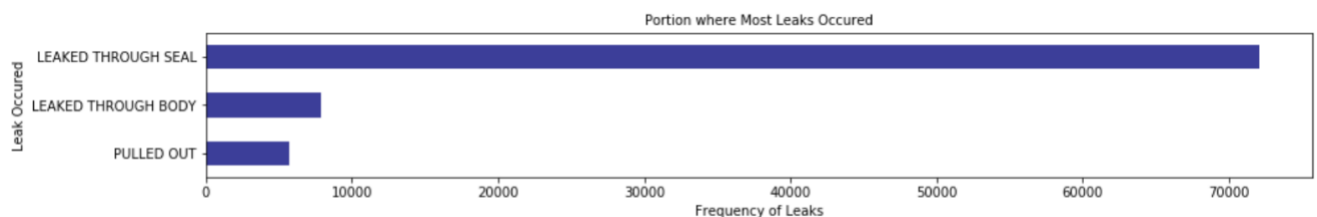
LEAK_CAUSE_TEXT	ADDITIONAL_LEAK_FEATURES	%_Feature_Count
MATERIAL OR WELDS/FUSIONS	MATERIAL DEFECT	9.033886
NATURAL FORCES	YES	7.503709
	NO	7.500204
MATERIAL OR WELDS/FUSIONS	DESIGN DEFECT	5.626613
EXCAVATION DAMAGE	AT TIME OF LEAK DISCOVERY	2.186635
	PREVIOUS TO LEAK DISCOVERY	0.275666



- **Portion where Most Leaks Occurred:**

****Portion where leak occurred****

	Occurred_Count	% Occurred_Count
LEAKED THROUGH SEAL	72062	84.173763
LEAKED THROUGH BODY	7867	9.189240
PULLED OUT	5682	6.636998



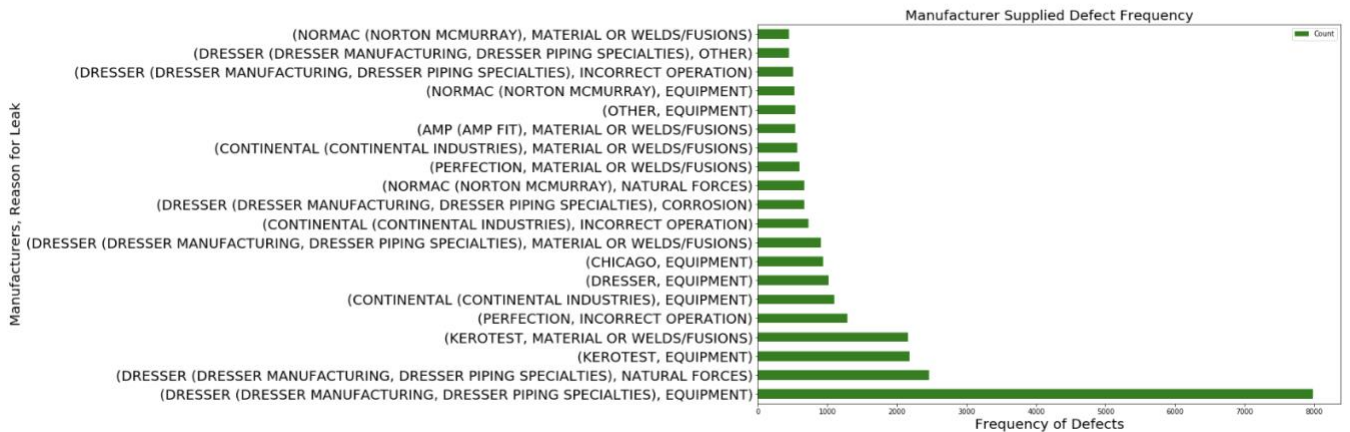
Observation Summary:

- 39.4K or 46% leaks were caused due to **equipment failure**, where features of failure were not known.
- 7.7k or 9% leak were caused due to **welding defects**.
- 72.1k or 84% **leaked through the seal**.

- Manufacturer Supplied Defects:

Manufacturer Supplied Defect Frequency:

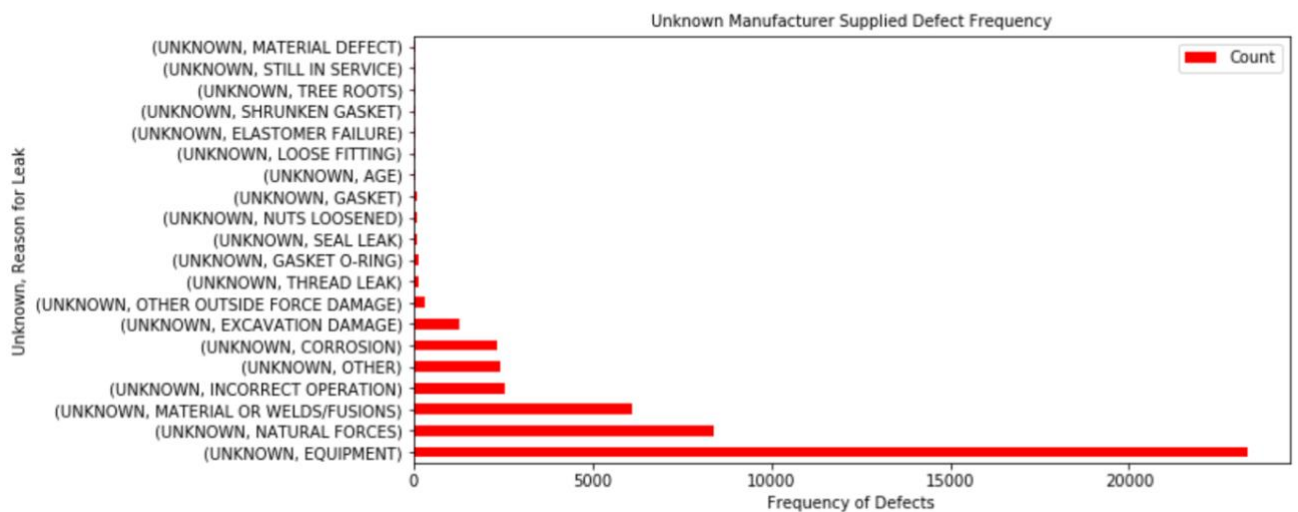
MANUFACTURE	LEAK_CAUSE_TEXT	Count
DRESSER (DRESSER MANUFACTURING, DRESSER PIPING ...	EQUIPMENT	7985
	NATURAL FORCES	2461
KEROTEST	EQUIPMENT	2177
	MATERIAL OR WELDS/FUSIONS	2162
PERFECTION	INCORRECT OPERATION	1285



- Unknown Manufacturer Supplied Defects:

Unknown Manufacturer Supplied Defect Frequency:

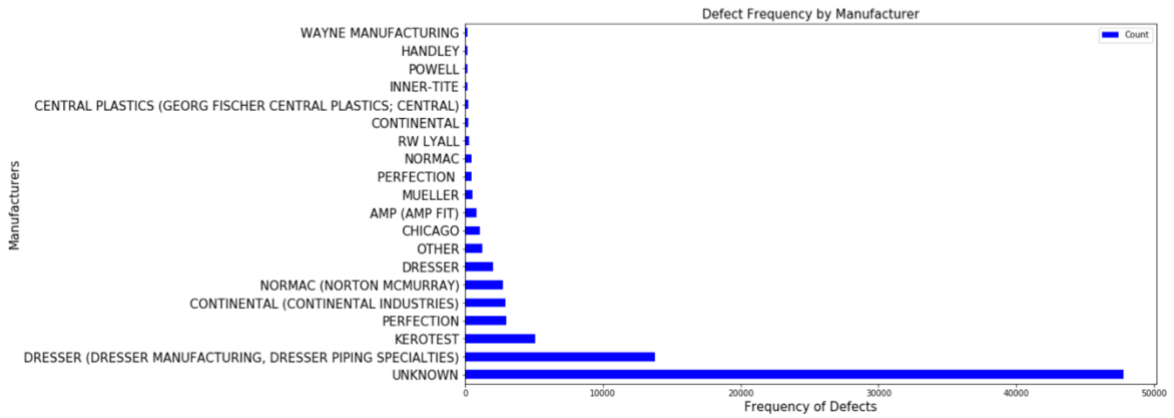
MANUFACTURE	LEAK_CAUSE_TEXT	Count
UNKNOWN	EQUIPMENT	23328
	NATURAL FORCES	8408
	MATERIAL OR WELDS/FUSIONS	6108
	INCORRECT OPERATION	2537
	OTHER	2434



• Defect Frequency by Manufacturers:

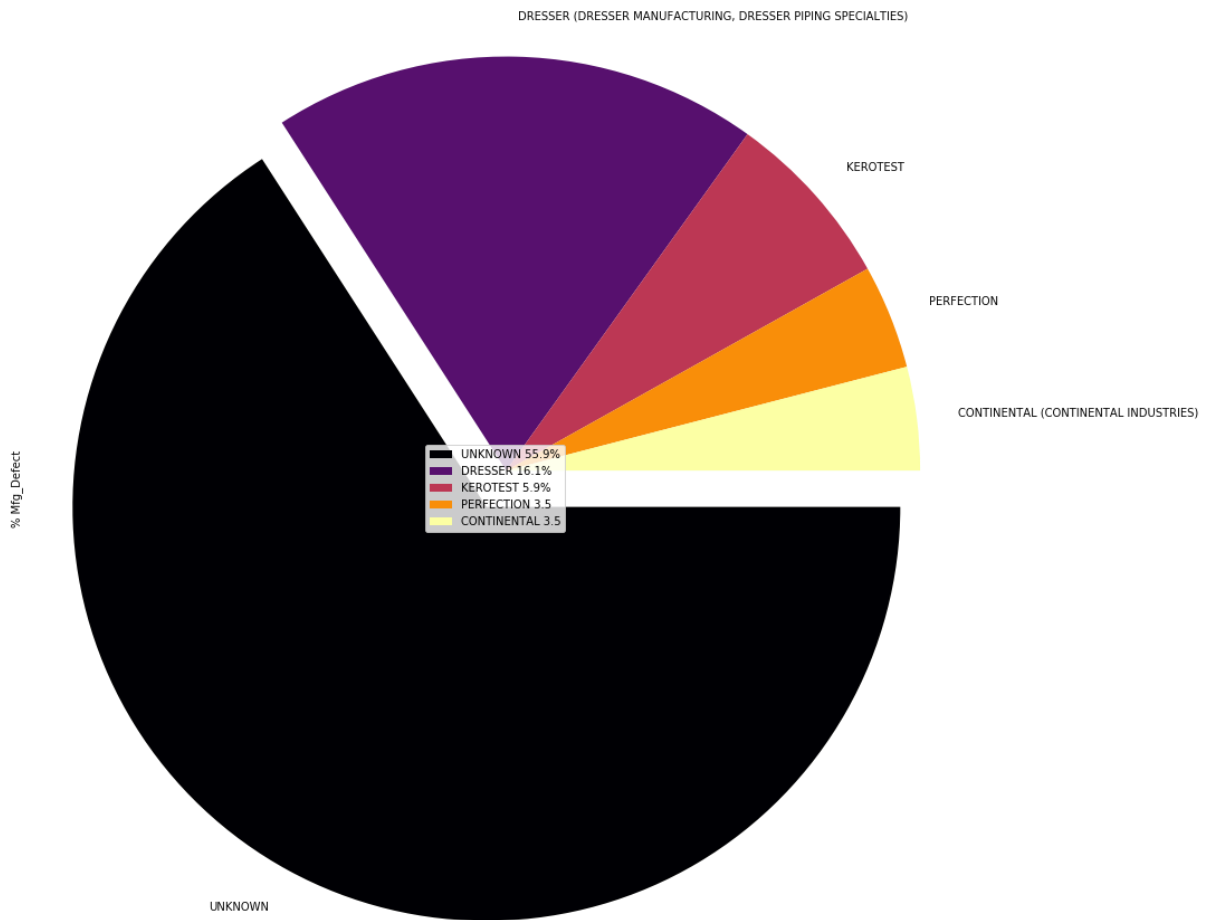
Defect Frequency by Manufacturer:

	Mfg_Count	% Mfg_Defect
MANUFACTURE		
UNKNOWN	47816	55.887234
DRESSER (DRESSER MANUFACTURING, DRESSER PIPING ...	13808	16.138760
KEROTEST	5073	5.929311
PERFECTION	2954	3.452629
CONTINENTAL (CONTINENTAL INDUSTRIES)	2928	3.422240



• Percentage of Defects by Manufacturer:

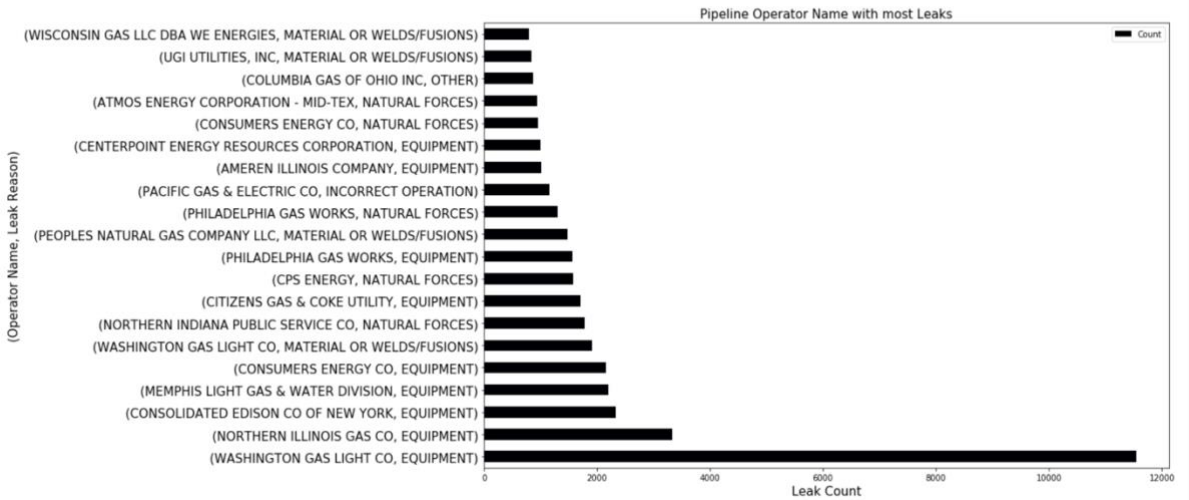
Percentage of Manufacturer Defects



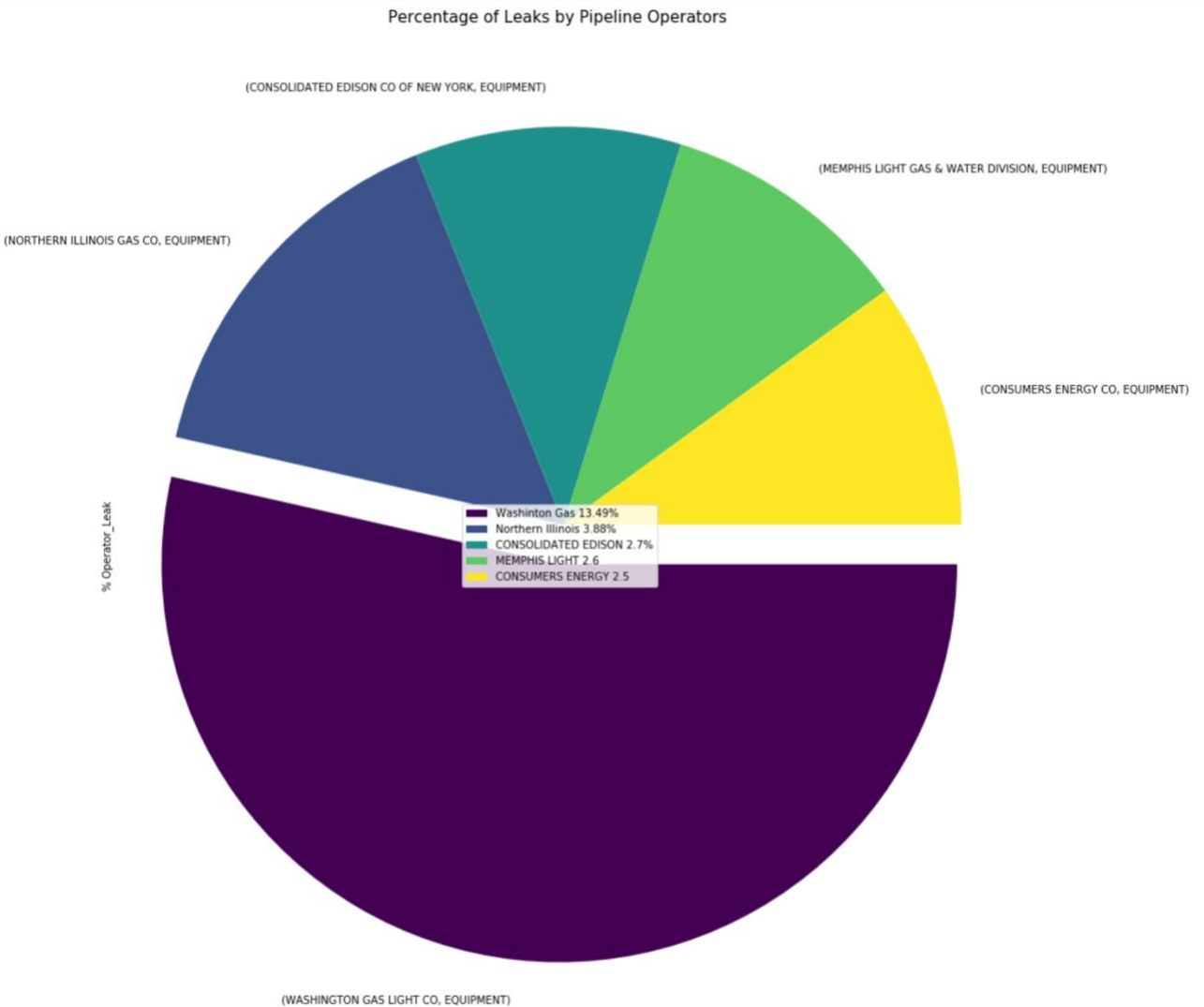
- Pipeline Leaks by Operator:

Leak Frequency by Pipeline Operator:

OPERATOR_NAME	LEAK_CAUSE_TEXT	Operator_Count	% Operator_Leak
WASHINGTON GAS LIGHT CO	EQUIPMENT	11551	13.492425
NORTHERN ILLINOIS GAS CO	EQUIPMENT	3326	3.885015



- Percentage of leaks by Pipeline Operators:



Observation Summary :

Manufacturers:

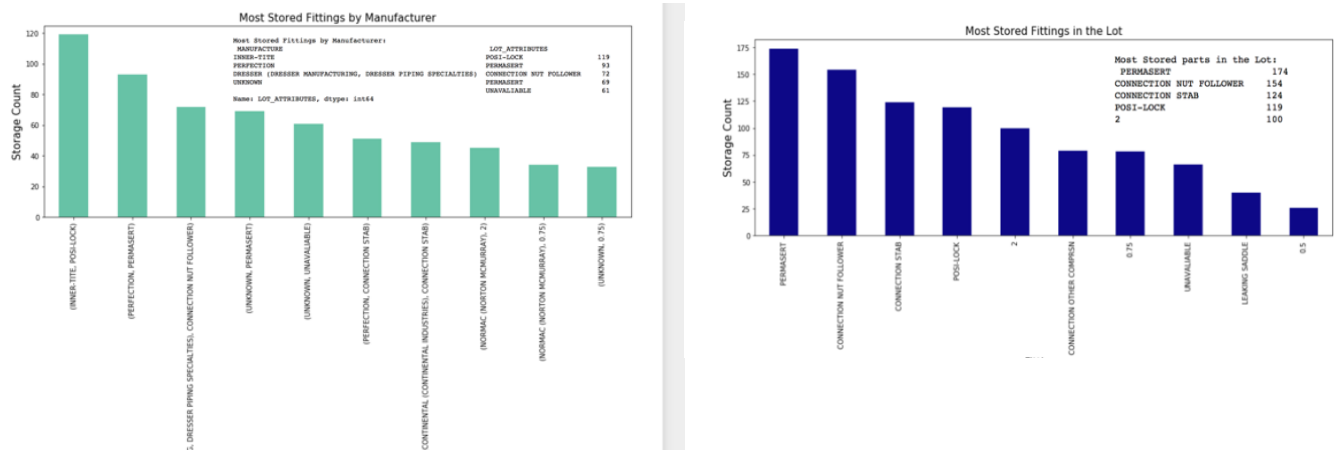
- 56% defects were caused by Unknown manufacturers, majority related to equipment failure.
- Dresser and Kerotest accounted for 16% and 6% defects related to equipment, natural forces and equipment, welding failures respectively.

Operators:

- Most pipeline operator leaks were due to equipment failure.
- Washington Gas Light and Northern Illinois pipeline operators recorded 13.49% and 3.88% leaks respectively.

Most Stored Fittings by Manufacturer and By Lot:

After cleaning lot attributes and exploring manufacturers, Permasert was observed to be the most stored fitting in the lot supplied by two Dresser and Perfection. While, per manufacturer basis Inter-Tite, the manufacturer of POSI-LOCK carried maximum fittings in the lot compared to other manufacturers.



Relationship between dates (Installation Vs Report Vs Filing):

It was observed that there was a significant delay (12 years +) between failure occurred date when compared to reported and filed date.

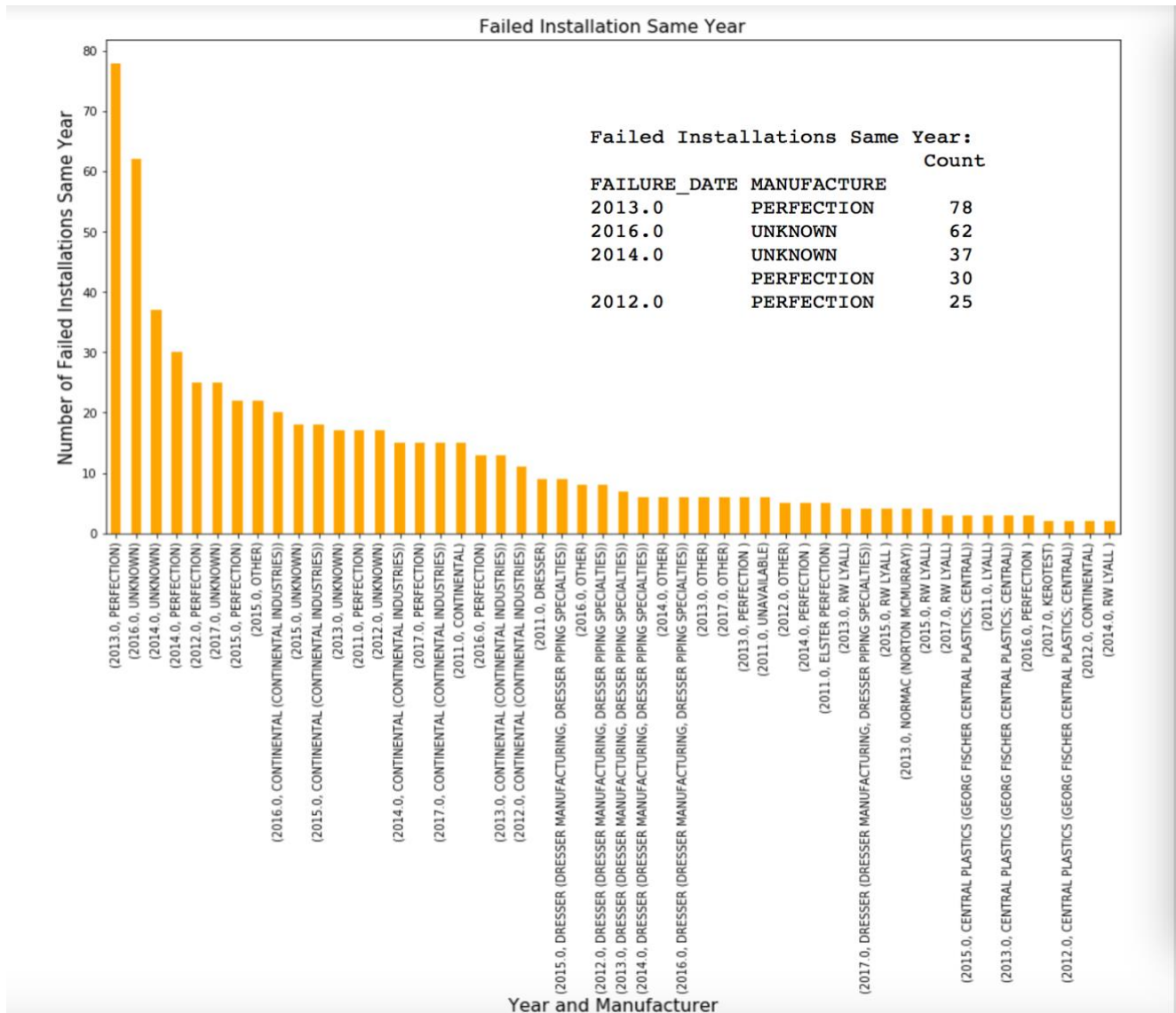
After further investigation, it was clear that majority of the reports were filed the same day as the failure date. Hence, filing date was corrected and matched with the failure date to avoid any date lag in our study.

Oldest Installation:

First Mechanical fitting was installed 165 years ago in the year 1851. There were 6 installations done back then by Unknown manufacturers

Same Year Failed Installation:

Interestingly, there were also installations which failed within the first year of installation as shown in the graph below:



Observation Summary:

1. Perfection had maximum number of failed installations in 2013.
2. Dresser, Continental and Perfection had multiple failed installations between 2011 to 2017 as shown in the graph above.

After exploratory analysis, 20 columns were dropped and 4 new feature columns were added to extract meaningful insights from the raw data.

Machine Learning:

In the final phase after data pre-processing, to prepare our data for modeling, it was important to check for missing and categorical values and see if it requires any further treatment.

There were still multiple missing values present in the dataset which had to be topped up by frequently occurring values a.m. mode values in the column or replaced with 'Unknown' where mode values presented a bias due to large amount of missing information.

A total of **155,047** values in various columns were replaced to completely avoid missing fields in the final table, df_cleaned.

In the last step before modeling, multiple categorical values had to be converted in to numerical values, which was done by using category encoding method discussed below:

1. One-hot-encoder.
2. Binary encoder.

The main difference between the two approaches was in terms of the data size it generated after conversion.

For example: One-Hot generated 3,912 columns after optimizing with label encoder while Binary Encoder generated 136 columns, which was significantly less when compared to one-hot encoder.

In order to evaluate the difference between the two approaches, I modeled two data sets separately, Model A (one-hot) and Model B (Binary) before applying machine learning model.

Model Selection:

Given the data structure, I decided to evaluate the two models using Random Forest Classifier. Random forests can handle unbalanced data, outliers and non-linearity well. The only drawback however is that it can overfit the data which can be managed by hyperparameter tuning.

To identify best hyper parameters for the model, I started with Randomized Search CV and finished selection using Grid Search CV. During this process, we made 90 fits and it took 1 hour and 9 minutes to get the following hyper parameters using Model B data.

Selected Hyper Parameters	Description
{'n_estimators': 100,	#Number of Trees
'min_samples_split': 10,	#Minimum samples required to split internal node
'min_samples_leaf': 1,	#Minimum samples at leaf node
'max_features': 100,	#Maximum features to consider for split decision
'max_depth': 50,	#Maximum depth of each tree
'criterion': 'entropy'}	#Quality of split

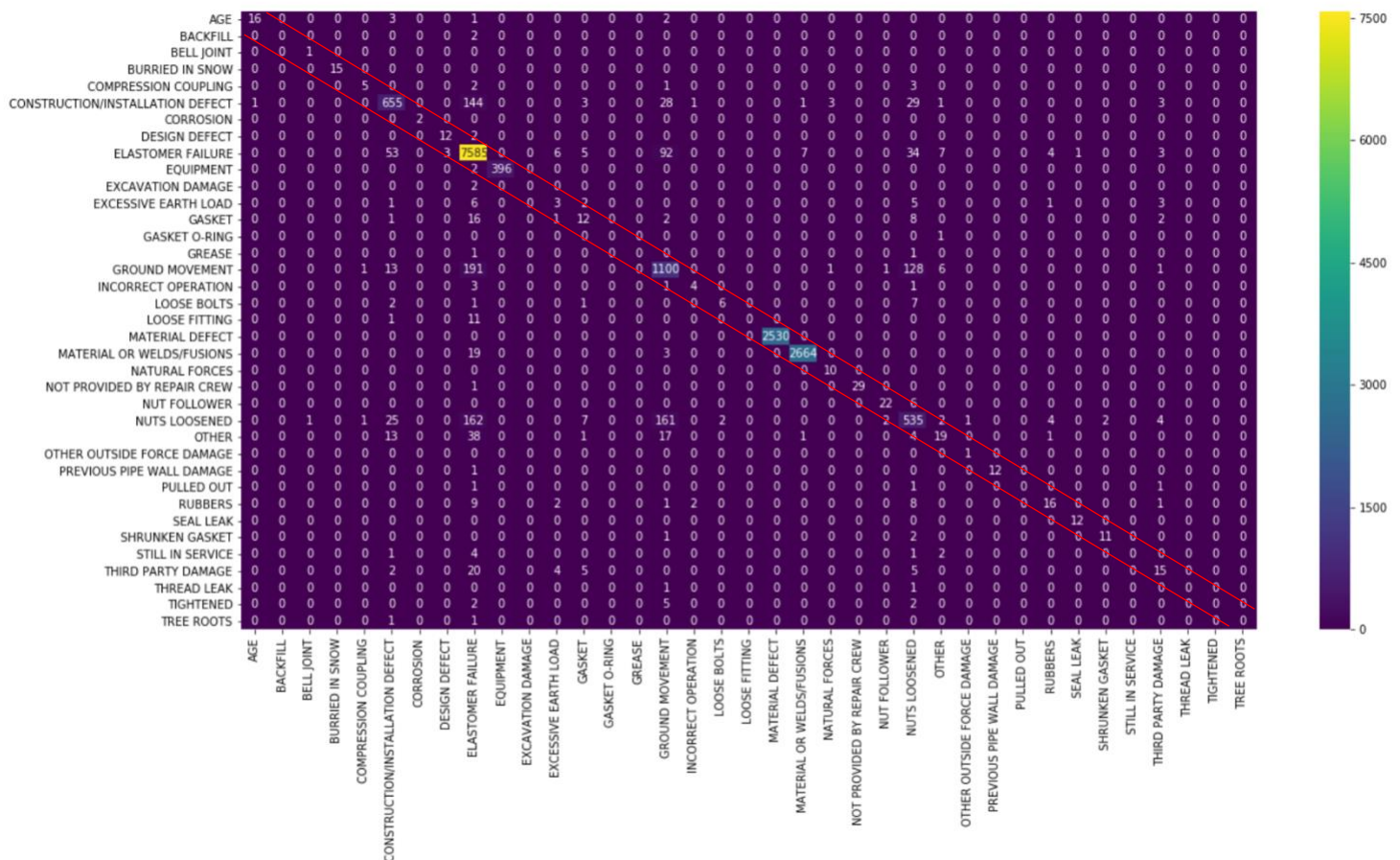
Model Evaluation:

Model B (Binary Encoded): As per classification report, we were able to train and classify 38 reasons that caused a mechanical fitting leak in the gas pipeline. Below is the classification report and a visual of confusion matrix, which will simply tell us how many correct and incorrect predictions for each leak label was made .

Classification Report:

	precision	recall	f1-score	support
AGE	0.94	0.73	0.82	22
BACKFILL	0.00	0.00	0.00	2
BELL JOINT	0.50	1.00	0.67	1
BURIED IN SNOW	1.00	1.00	1.00	15
COMPRESSION COUPLING	0.71	0.45	0.56	11
CONSTRUCTION/INSTALLATION DEFECT	0.85	0.75	0.80	869
CORROSION	1.00	1.00	1.00	2
DESIGN DEFECT	0.80	0.86	0.83	14
ELASTOMER FAILURE	0.92	0.97	0.95	7800
EQUIPMENT	1.00	0.99	1.00	398
EXCAVATION DAMAGE	0.00	0.00	0.00	2
EXCESSIVE EARTH LOAD	0.19	0.14	0.16	21
GASKET	0.33	0.29	0.31	42
GASKET O-RING	0.00	0.00	0.00	1
GREASE	0.00	0.00	0.00	2
GROUND MOVEMENT	0.78	0.76	0.77	1442
INCORRECT OPERATION	0.57	0.44	0.50	9
LOOSE BOLTS	0.75	0.35	0.48	17
LOOSE FITTING	0.00	0.00	0.00	12
MATERIAL DEFECT	1.00	1.00	1.00	2530
MATERIAL OR WELDS/FUSIONS	1.00	0.99	0.99	2686
NATURAL FORCES	0.71	1.00	0.83	10
NOT PROVIDED BY REPAIR CREW	1.00	0.97	0.98	30
NUT FOLLOWER	0.88	0.79	0.83	28
NUTS LOOSENEED	0.69	0.59	0.63	909
OTHER	0.50	0.20	0.29	94
OTHER OUTSIDE FORCE DAMAGE	0.50	1.00	0.67	1
PREVIOUS PIPE WALL DAMAGE	1.00	0.92	0.96	13
PULLED OUT	0.00	0.00	0.00	3
RUBBERS	0.62	0.41	0.49	39
SEAL LEAK	0.92	1.00	0.96	12
SHRUNKEN GASKET	0.85	0.79	0.81	14
STILL IN SERVICE	0.00	0.00	0.00	8
THIRD PARTY DAMAGE	0.45	0.29	0.36	51
THREAD LEAK	0.00	0.00	0.00	2
TIGHTENED	0.00	0.00	0.00	9
TREE ROOTS	0.00	0.00	0.00	2
micro avg	0.92	0.92	0.92	17123
macro avg	0.55	0.53	0.53	17123
weighted avg	0.91	0.92	0.91	17123

Confusion Matrix:



Confusion matrix shows, counts outside of the two diagonal lines as mixed classification labels.

Feature Importance:

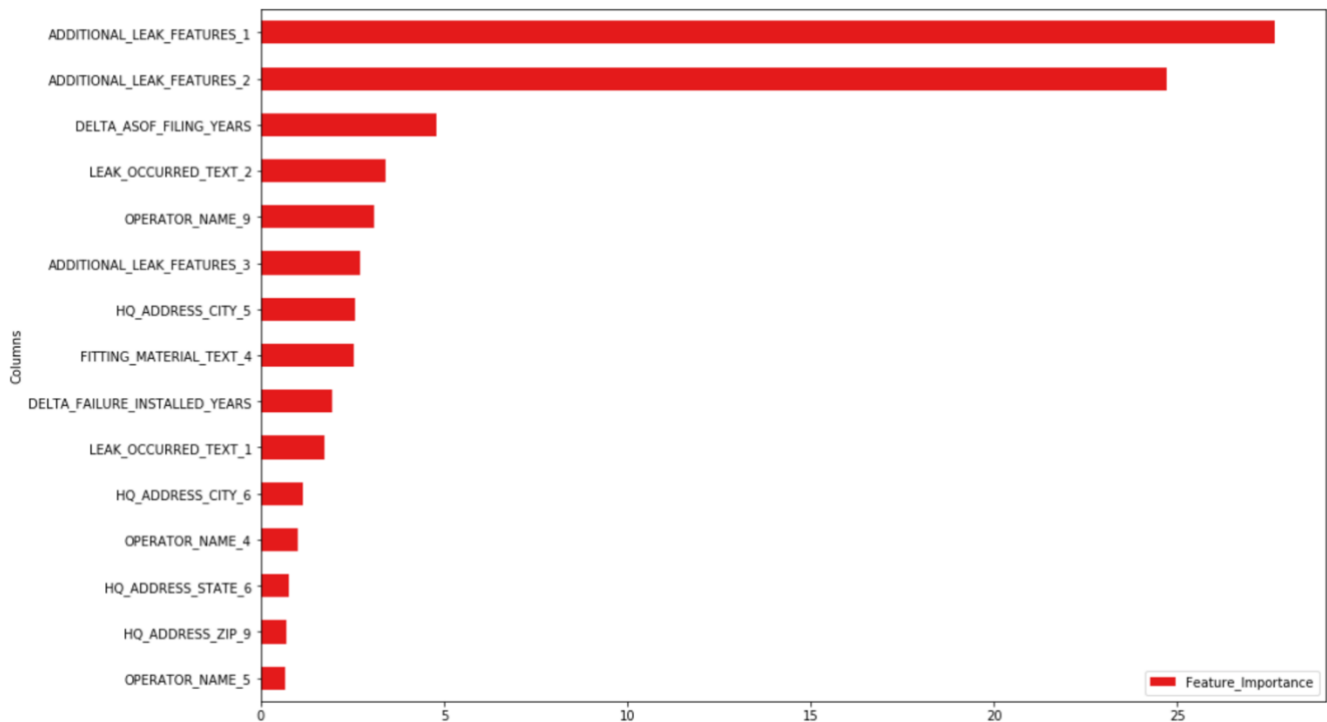
Classifier shows top 15 important features which contributed 79.9% in predicting leak cause in the pipeline with 91.6 accuracy.

Top 15 Features for Classifying Leaks in Pipeline:
 Feature_Importance 79.525348
 dtype: float64

Feature_Importance	
Columns	
ADDITIONAL_LEAK_FEATURES_1	27.665679
ADDITIONAL_LEAK_FEATURES_2	24.703340
DELTA_ASOF_FILING_YEARS	4.783924
LEAK_OCCURRED_TEXT_2	3.396982
OPERATOR_NAME_9	3.096549
ADDITIONAL_LEAK_FEATURES_3	2.719892
HQ_ADDRESS_CITY_5	2.588522
FITTING_MATERIAL_TEXT_4	2.554088
DELTA_FAILURE_INSTALLED_YEARS	1.934990
LEAK_OCCURRED_TEXT_1	1.751176
HQ_ADDRESS_CITY_6	1.153430
OPERATOR_NAME_4	1.029005
HQ_ADDRESS_STATE_6	0.767364
HQ_ADDRESS_ZIP_9	0.716673
OPERATOR_NAME_5	0.663734

Distribution of top 15 features used in classifying pipe leaks:

<matplotlib.axes._subplots.AxesSubplot at 0x7f8403617240>



Model A (one-hot):

Using same hyper-parameters, Model A resulted in comparable model accuracy 90.4% and leak cause classification prediction. However, it took longer run time and required way more features compared to Model B.

Conclusion:

- Random Forest using Binary Encoded Data (Model B) classified top 15 causes for leak with 91.6% accuracy.
- Random Forest using one-hot encoded data (Model A) classified top 15 causes for leak with 90% accuracy.
- Model B run time was faster than Model A due to significant difference in column sizes (136 Vs 3,912)
- Model B used top 15 features to predict 79.9% of the leak classification while Model A classified only 48.8%.
- Random Forest using Binary Encoder (Model B) was preferred.
- Important Features which classified leak cause correctly were:
 - Excavation damages
 - Natural forces
 - Welding defects
 - Leak Through the Body or Seal
 - Time elapsed between 'Installation' and 'Failure Date'.

- Time elapsed between 'As of' and 'Filing Date'
- Pipeline Operator

Future Improvements:

Existing Model: Even though Model B accuracy score is 91.6%, there were areas of mixed classification which could be improved in future models.

Example: Elastomer Failure had 7,642 examples where Leak was identified due to elastomer failure. However, it also had 144 examples of construction/installation defects, 191 examples of ground movement defects and 162 examples of Nuts Loosened defects under the same class.

We would need to check with SME's to see if elastomer failure could be caused due to these examples.

Moreover, exploratory analysis showed significant reasons for leak caused due to equipment failure. We would need equipment data to understand which equipment features led to fitting failure in the past, which is currently not known.

Apply Other Advanced Models: I would like to run deep learning model on the same dataset and compare leak classification result. Also, use predictive modeling to estimate when a mechanical fitting could fail based on the number of years of operations.

Build Dashboard: I would like to build a real-time dashboard on key performance indicators such as expected failure date, operator and manufacturer details, and likely reason for leak cause, to help clients avoid any operational risks, early-on.

---End of Project Report---